EFFECTS OF EDUCATION ON THE INTERGENERATIONAL TRANSMISSION OF LABOR INCOME IN MEXICO

Jorge N. Valero-Gil
Universidad Autónoma de Nuevo León

and

José A. Tijerina-Guajardo
Universidad Autónoma de Nuevo León

INTRODUCTION

This paper studies the relationship between the labor market earnings of parents and their children to understand how education affects the intergenerational earnings distribution. The relation between the income of parents and their offspring has been extensively reviewed by Becker and Tomes [1986] who extended the theoretical analysis to include the intergenerational transmission of endowments. In Mexico the problem of intergenerational mobility has been studied for wages by Valero-Tonone [1999] and for education by Binder and Woodruff [1999].

In this paper we incorporate heterogeneity in the transmission mechanism of earnings by grouping families according to the level of family income. We also allow heterogeneity by using quantile regressions to examine how the new income distribution evolves following Eide and Showalter [1999]. We then discuss the influence of education on the distribution of hourly wages across generations.

Most of the papers on the intergenerational transmission of earnings use a measure of income or hourly wages for both generations [Eide and Showalter, 1999; Binder and Woodruff, 1999]. However, we separate the earnings of the head of the family (our approximation for parents) into the expected earnings and a residual. The expected earnings are estimated using an earnings function that depends on schooling and work experience. Essentially, this is equivalent to distinguishing earnings that depend on a weighted average of earnings for the population, given a level of human capital, from earnings of the head of the family due to other unobservable factors. It is similar to Galton's [1886] determination of height as an average of the population height and that of the parents. The expected parental income is a variable that depends on the years of education—that could be subject to public policy—which in turn affects the earnings distribution of their children 25 years from now.

Jorge N. Valero-Gil: Facultad de Economía, Universidad Autónoma de Nuevo León, Loma Redonda 1515-A Pte., Col, Loma Larga, Monterrey, NL, Mexico CP 64710. E-mail: jvalero@ccr.dsi.uanl.mx

Eastern Economic Journal, Vol. 28, No. 3, Summer 2002

Following Becker and Tomes [1986], we expected lower rates of return on schooling for families with higher income. This is so because in the absence of a perfect capital market to fund education, poor families are less able than rich families to finance the education of their children. Our estimates, however, show that in Mexico the rate of return to education increases with income. These results are consistent with the multiplicative model of Goldberger [1989], with that of Hang and Mulligan [2000], and with the empirical work for Canada by Corak and Heisz [1999]. They are also consistent with Becker and Tomes [1986] if one assumes that the higher the earnings of the head of household, the greater the ability, on average, of children.

Our hypothesis is that the relationship between the earnings of the parents and their children depends on both where the parent's income is located within the income distribution, and on the distribution of earnings of their children. To deal with the first issue, we divided the sample into four parts according to the level of household income. For the second point we use quantile regressions. For the United States, Eide and Showalter [1999] found that parental income had a greater effect on the earnings of their children at the bottom of the earnings distribution. However, for Mexico we found that parental income had a greater effect on children at the top of the earnings distribution. A similar result arises if schooling is included; higher returns to formal education are observed for children at the top of their earnings distribution.

The importance of parental education on the next generation's distribution of income—and of the relative importance of the corrections through education—have been found in different ways in other contexts. Heckman [2000] summarizes recent findings about how "background factors"—and not income directly—are the main indicators that are related to the education of the new generation and to their success. The discussion of background factors has also been present in the context of racial differences in earlier studies by Freeman [1981] and Welch [1990].

This paper is organized as follows. In the next section we discuss the sample and the effects of labor market experience on the intergenerational transmission of earnings. As it is shown, as the children's labor market experience grows, the coefficient for the intergenerational transmission decreases. We use cross sectional data given data limitations; however, we are aware that the impact of parental income on the earnings of children is likely to change over time. In the third section, we discuss the model and present some preliminary results. The main point is that education, which can be a public policy variable, has a significant effect on the intergenerational transmission coefficient. In section four, we extend the analysis by grouping families according to the level of income of parents, and in section five we use quantile regressions along the lines of Eide and Showalter [1999]. The return to education is higher as either the income of the family or of the children rises. The last section provides some concluding remarks.

THE SAMPLE AND THE EFFECT OF EXPERIENCE

We use microdata from the National Urban Employment Survey, conducted by INEGI and the Secretaría del Trabajo y Previsión Social [INEGI and STPS, 1998]. Each observation represents a household, whose head of family is the source of information for generation 0. Own children living in the same home who report earnings represent generation 1. The number of observations with complete data in both generations is 14,437. The information on children is collected for those aged 12 years or older who live in the same household with the family head. As a measure of earnings we use the log hourly wage. Years of schooling is used to measure education (*edu*) and labor market experience is defined as age minus education minus six.

Because we do not have panel data, we cannot compare the earnings of parents and children at the same age. Thus, to examine the intergenerational effects, we regress information of the children against the earnings of the head of household. In order to control for the effects of labor market experience, we include the experience of the head of household as a regressor in the earnings equation of children. The general form of the earnings equation for children is as follows:

$$w_{ch} = \alpha_0 + \beta_0 w_h + \alpha_1 exp_{ch} + \alpha_2 exp_{ch}^2 + \beta_1 exp_h + \beta_2 exp_h^2 + \varepsilon_{ch} \tag{1}$$

where w_{ch} is the log-hourly wage of children; w_h is the log-hourly wage for the head of household; exp_{ch} and exp_{ch}^2 are the labor market experience and experience squared of children, respectively; exp_h and exp_h^2 are the labor market experience and experience squared of the household head, respectively; and ε_{ch} is an error term.

Table 1 presents the results of estimating equation (1) for different levels of children's labor market experience. The results for the regression between the log wage of children on the earnings of the head of family is in column 1; an increase in the hourly-wage of the head of household of 10 percent will increase the hourly wage of their children by 3.38 percent. This estimate is within the range of those discussed by Becker and Tomes [1986, Table 1]. In column 2 a correction is made for experience, by including the labor market experience of the head of the family as well as that of children. Notice that if the regression for children is $w_{ch} = \alpha_0 + \alpha_1 exp_{ch} + \alpha_2 exp_{ch}^2 + \varepsilon_{ch}$ and the regression for heads of household is $w_h = \beta_0 + \beta_1 exp_h + \beta_2 exp_h^2 + \varepsilon_h$, then we are running ε_{ch} on ε_h in column 2 of Table 1. That is, we are comparing the lifetime earnings paths of parents and children at time 0.

Even though we do not have panel data that would allow us to compare the earnings of parents and children at the same age, we can obtain estimates about the intergenerational transmission as generation 1 members gain experience in the labor market. The results for at least 1, 2, 4, 9 and 17 years of experience in the labor market for generation 1 are presented in columns 3 to 7. They show that even when the relationship between earnings is declining, it is statistically different from zero. Apparently the heads of families can influence their children and significantly improve their initial performance in the labor market.

Our results could be potentially biased if the length of time children stay at home varies according to family income. To account for this possibility, we excluded from the sample families with two heads living in the same household. Moreover, in order to capture the lifetime earnings path of members of generation 1, we also exclude cases with less than two years of experience and with less than 20 hours of worked a week. The results with these exclusions are shown in column 8 and they are comparable to those reported in column 2. Therefore, we use this sub-sample in the subsequent analysis in order to avoid spurious results.

TABLE 1
Earnings of Children and Labor Market Experience
Dependent Variable: log Hourly Wage for Children

			Labor Market Experience for Children of at Least					
	All	**All**	**1 year**	**2 years**	**4 years**	**9 years**	**17 years**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
w_h	0.338	0.360	0.352	0.345	0.331	0.306	0.271	0.360
	(57.9)	(60.4)	(56.7)	(52.7)	(44.5)	(25.4)	(9.8)	(61.0)
exp_{ch}		0.018	0.019	0.020	0.019	0.013[a]	0.038[a]	0.022
		(8.3)	(7.5)	(7.1)	(4.9)	(1.4)	(1.0)	(10.2)
exp_{ch}^2		−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
		(−6.5)	(−6.4)	(−6.2)	(−5.0)	(−2.3)	(−1.3)	(−8.0)
exp_h		0.024	−0.001	-0.001	0.015	0.006[a]	−0.004[a]	0.028
		(7.2)	(−6.4)	(5.6)	(3.3)	(0.7)	(−0.2)	(8.5)
exp_h^2		−0.0002	−0.0002	−0.0002	−0.0001	0.0000[a]	0.0002[a]	−0.0003
		(−4.7)	(−4.8)	(−3.7)	(−1.9)	(0.1)	(0.8)	(−6.0)
Constant	1.108	0.423	0.405	0.489	0.656	0.924	0.773[a]	0.293
	(84.9)	(6.9)	(6.1)	(6.8)	(7.5)	(5.1)	(1.3)	(4.8)
N	18940	18629	16785	15119	11422	4361	735	17399
R^2 adj.	.15	.17	.17	.16	.15	.13	.12	.19

a. Coefficients are NOT statiscally different from zero at 5 percent level of confidence.
Column 8: Regression equation for children working 20 hours or more a week, and with at least two years of labor market experience. t-statistics values in parentheses.

THE MODEL AND RESULTS FOR THE SUB-SAMPLE

The Galton model, according to Goldberger [1989, 505] says that height is determined by both the height of parents and the height of their ancestors. A similar model can be used to model the transmission of income. We assume that the earnings of children are a weighted average of the population mean earnings given a level of education, and the earnings of their parents. The simple model says that,

$$w_{ch} = a + b\, w_h + u_{ch} \tag{2}$$

where w_{ch} is determined by the income of the parents (w_h) plus an error and a constant. We can consider that the income of the parent is composed of the sum of two parts: the expected population income, given his education and experience in the labor market, and an error term:

$$w_h = w_{h\text{-}hat} + \upsilon_h \tag{3}$$

where

$$w_{h\text{-}hat} = c_0 + c_1\, edu_h + c_2\, exp_h + c_3\, exp_h^2 \tag{4}$$

TABLE 2
Earnings of Children with Working and Non-Working Parents
Dependent Variable: Log Hourly-Wage for Children

	Working Head						Non-Working Head	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
w_h	0.344	0.232						
	(53.3)	(38.3)						
$w_{h\text{-}hat}$			0.673	0.295	0.721	0.363	0.620	0.201
			(53.6)	(21.3)	(59.5)	(26.8)	(27.1)	(8.4)
υ_h					0.243	0.211		
					(35.8)	(33.3)		
edu_{ch}		0.082		0.079		0.074		0.085
		(60.4)		(49.6)		(47.7)		(35.4)
Constant	0.406	0.165	−0.558	−0.080[a]	−0.566	−0.120[a]	−0.115[a]	0.183
	(5.8)	(2.6)	(−7.4)	(−1.1)	(−7.8)	(−1.7)	(−0.7)	(1.3)
N	14437	14437	14437	14437	14437	14437	5677	5677
R^2 adj.	.17	.34	.17	.29	.24	.35	.13	.28

t-statistics values in parentheses.
Other variables included are: exp_{ch}, exp_{ch}^2, exp_h, and exp_h^2.
a. coefficients are NOT statiscally different from zero at 5 percent level of confidence.

c_0, c_1, c_2 and c_3 are the estimated coefficients in a linear regression for working parents; edu_h refers to years of schooling and experience (exp_h) is approximated by $age - edu_h - 6$. The error υ_h contains the personal characteristics of the head of household (other than schooling and experience) and the characteristics of their job and region. We assume that the effect of $w_{h\text{-}hat}$ is different from that of the error. Then we can rewrite the model as:

$$w_{ch} = \alpha + \beta_1 w_{h\text{-}hat} + \beta_2 \upsilon_h + \beta EXP + w_{ch} \tag{5}$$

where *EXP* contains the experience variables for children and parents. With the presence of *EXP* in the regression, the coefficient β_1 will reflect the net effect of parental education.

Distinguishing between β_1 and β_2 is relevant because $w_{h\text{-}hat}$ can be manipulated through public policy. Behrman and Taubman maintain that the earnings correlation will provide an upper bound to the true earnings correlation "because parental tastes and wealth influence offspring's schooling much more than their adult earnings capacity" [1985, 147]. Even though they consider that schooling is determined for the most part by family characteristics, both genetic and environmental, we consider that schooling, an element that can be subject to public policy, could correct earnings inequality in the population, along the lines argued by Tanzi [1998].

The results from estimating equation (5) are reported in Table 2.[1] Columns 1 and 2 present the regression for the earnings of children along the lines of Eide and Showalter [1999]. As can be observed from column 1, an increase of one percent in the hourly wage of the head will increase the hourly wage of his offspring by 0.344 percent.[2] Alternatively, a child whose head of household earns 100 percent above the mean could expect to be above the mean earnings level of his generation by 34.4 percent.

We now introduce education as a regressor in column 2. The role of education is clearly seen by the reduction in the coefficient of generation 0 earnings to 0.232. Eide and Showalter [1999, Table 2] found a similar change for the United States from 0.34 to 0.24 when schooling was included. The coefficient is significantly different from zero, showing that an important part of the intergenerational transmission of earnings is undertaken through formal education. In other words, given the formal schooling of children, the effect of parents' wages on their children's earnings is reduced; alternatively, schooling can be seen as a means to enhance the opportunity for children to attain higher levels of earnings.

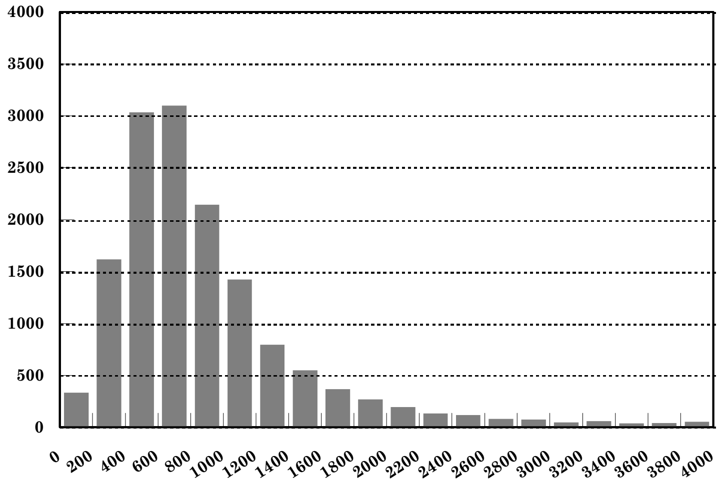
In columns 3 and 4 we perform a similar estimation, but substitute the observed earnings of generation 0 by their expected earnings, given their specific characteristics. The explanatory variable is the log hourly wage estimated for the head of the family.[3] This coefficient is estimated as 0.673, showing a greater effect of the expected earnings of parents and the earnings of children than the observed earnings. In other words, regression to the mean earnings becomes slower. However, this coefficient changes to 0.295 when the schooling of children is included.

On the other hand, columns 5 and 6 show the complete model, with the variables $w_{h\text{-}hat}$, $\upsilon_{h,}$ and edu_{ch}. As expected, the coefficient of w_h in columns 1 and 2 is bounded by the coefficients $w_{h\text{-}hat}$ and υ_h. The coefficients for $w_{h\text{-}hat}$ and υ_h are statistically different from zero at 5 percent level of confidence, and the expected earnings of parents has a larger weight. If the schooling of the children is zero, an increase of one percent of a parent's expected earnings will increase the children's earnings by 0.721 percent.[4] In this case, the inequality in earnings within a generation will be reduced (holding other things constant) to around 25 percent in four generations.[5] However, when we include schooling, the coefficient for the expected earnings of parents drops to 0.363, pointing out the potential role of human capital (in terms of formal education) on the intergenerational inequality of earnings.

The coefficient of υ_h does not significantly change when we include the variable education, either in Table 2 nor in Tables 3 and 4, as we show below. With the exception of education and experience, education of the children does not correct the transmission mechanism of the parent's wage associated with υ_h that includes individual characteristics of the parents. The variables υ_h and edu_{ch} are nearly orthogonal, that is, they give independent information about the hourly wage of generation 1. The coefficient of $w_{h\text{-}hat}$ that represents the relative return to education of generation 0 on the hourly wages of generation 1 is the one which is modified by edu_{ch} .

Columns 7 and 8 show the coefficients for children with nonworking heads of family. Even when the head does not have an observed salary, the coefficient for the expected earnings is 0.620, and it is not statistically different from the coefficient 0.673 in column 3. This result shows the importance of the average investment on formal education and, thus, provides support to the model we employ.

FIGURE 1
Histogram of "Family Monthly Income" 1997



Excludes observations with *ingper* equal to zero or greater than 4000 pesos.

EARNINGS TRANSMISSION BY INCOME LEVELS

Schooling is an important factor determining the intergenerational transmission of earnings. However, it may be the case that people with different levels of income could have different quality of education or different endowments and, therefore, the impact of formal education may vary. The discussion about the possibility of measuring the importance of different endowments has been summarized by Goldberger [1989] and Becker [1989].

Hang and Mulligan [2000] have shown that it may not be possible to know the endowment coefficients if people are heterogeneous. Thus, it seems reasonable to assume that the analysis of the children's sample by family income levels may help determine the differential effect of schooling among people of the same generation. This is especially true if one considers that the lack of opportunity for children to acquire a formal education may come from the lack of income of their parents and imperfect capital markets for education.

To examine this problem we analyze four income groups. We looked for a variable with two characteristics: it should be different from the earnings of the head of the family and it should not include information about the earnings of the children (our dependent variable). Thus, to form the groups we generate the variable *ingper*. This variable is defined as the monthly earnings of the other members of the family, divided by the number of persons (more than 11 years old) in the household minus one; that is, we considered only the information of the rest of the family living in the household.

The distribution of *ingper* is shown in Figure 1, which excludes the long right tail with the cases with income levels greater than 4,000 pesos.[6] The groups were formed

TABLE 3
Earnings of Children Grouped by Level of Income
Dependent Variable: Log Hourly Wage for Children

	Group 1		Group 2		Group 3		Group 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$w_{h\text{-}hat}$	0.515	0.230	0.522	0.242	0.622	0.229	0.789	0.366
	(19.5)	(8.5)	(22.7)	(10.1)	(25.3)	(8.5)	(8.5)	(3.7)
v_h	0.155	0.149	0.171	0.147	0.128	0.115	0.167	0.163
	(12.2)	(12.4)	(13.4)	(12.2)	(8.2)	(8.0)	(3.4)	(3.5)
edu_{ch}		0.068		0.063		0.081		0.103
		(25.4)		(26.5)		(26.7)		(8.5)
Constant	-0.045^{a}	0.241	-0.084^{a}	0.243	-0.474	0.003^{a}	-0.554^{a}	-0.189^{a}
	(-0.3)	(2.0)	(-0.7)	(2.3)	(-3.2)	(0.0)	(-1.0)	(-0.4)
N	4937	4937	5180	5180	3876	3876	444	444
R^2 adj.	0.096	0.200	0.113	0.220	0.155	0.286	0.155	0.273

The groups formed were in the following ranks: Group 1: 0.01 to 600 pesos; Group 2: 600 to 1,000; Group 3: 1,000 to 3,000; Group 4: 3,000 pesos or more. t-statistics values in parentheses.
a. coefficients are NOT statiscally different from zero at 5 percent level of confidence.
Other variables included are: exp_{ch}, exp^2_{ch}, exp_h *and* exp^2_h.

according to the monthly earnings: 0.01 to 600 pesos (which correspond to the mode, with 28 percent of the sample); 600 to 1,000 (28 percent of the sample); 1,000 to 3,000 (36 percent), and 3,000 pesos or more (8 percent). The Pearson correlation of *ingper* with the log hourly wage of the head of the family is 0.48.

The results of estimating the model by income levels are shown in Table 3. Columns 1, 3, 5 and 7 show that the coefficient of $w_{h\text{-}hat}$ increases with income levels from 0.515 to 0.789. The intergenerational transmission coefficient persists more in time in families with higher income than in families with lower income levels. This result differs considerably from that presented by Eide and Showalter [1999] for the United States, where the relevance of the transmission coefficient diminishes as the level of income increases.

This result is not surprising. Becker and Tomes have argued that: "There is evidence that the influence of family background on the achievements of children is greater in less developed countries that it is in the United States. For example, father's education has a greater effect on son's education in both Bolivia and Panama than in the United States" [1986, S31]. In our model, father's education is included in the estimation of expected earnings of parents which may reflect the argument posed by Becker and Tomes.

On the other hand, when we include the variable schooling, we observe that the returns to education are increasing with the level of income. This result may have its origin on the better education of people with higher income levels, or on differences in parental endowments. The education levels of heads of the family (included indirectly via $w_{h\text{-}hat}$) and of the children, tend to redistribute income in favor of children from high income families.

The increasing return to schooling contrasts sharply with the expected return from Becker and Tomes [1986] model, where high levels of income are positively re-

TABLE 4
Quantile Regressions: Intergenerational Earnings Transmission
Dependent Variable: Log Hourly-Wage for Children

Quantile	0.3		0.5		0.6		0.9		0.95		0.98	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$w_{h\text{-}hat}$	0.567	0.300	0.661	0.338	0.708	0.365	0.951	0.438	1.027	0.478	1.077	0.540
	(41.4)	(18.4)	(48.2)	(21.2)	(47.2)	(21.7)	(40.3)	(18.0)	(29.2)	(12.9)	(19.2)	(10.5)
υ_h	0.217	0.188	0.250	0.212	0.260	0.221	0.264	0.240	0.255	0.224	0.276	0.222
	(27.3)	(24.4)	(32.5)	(28.3)	(31.2)	(28.0)	(18.6)	(19.1)	(11.7)	(11.5)	(7.4)	(7.8)
edu_{ch}		0.062		0.070		0.074		0.090		0.093		0.095
		(34.3)		(38.7)		(38.1)		(29.3)		(19.5)		(14.1)
Constant	−0.441	−0.150[a]	−0.292	0.025[a]	−0.277	0.059[a]	−0.327	0.205	−0.282[a]	0.133[a]	−0.122[a]	0.472
	(−5.3)	(−1.8)	(−3.5)	(0.3)	(−3.1)	(0.7)	(−2.1)	(1.8)	(−1.2)	(0.7)	(−0.3)	(2.0)
Pseudo R^2	0.094	0.141	0.117	0.174	0.127	0.190	0.201	0.286	0.211	0.303	0.206	0.304

t-statistics values in parentheses.
a. coefficients are NOT statiscally different from zero at 5 percent level of confidence.
Other variables included are: exp_{ch}, exp^2_{ch}, exp_h *and* exp^2_h. $N = 14437$ cases.

lated to the number of years of schooling and this, in turn, is therefore related to lower returns to education. It is also inconsistent with the estimations by Eide and Showalter [1999] for the United States.

However, it does not preclude its empirical validity as discussed by Becker and Tomes [1986], making reference to Bolivia and Panama. It may also be consistent with recent estimations on the increasing return to schooling at higher levels of education for Mexico [Valero-Gil, 1995; Meléndez-Barrón, 1997].[7]

EARNINGS TRANSMISSION USING QUANTILE REGRESSIONS

An alternative approach that can be used to analyze the transmission mechanism of earnings is the quantile regression method. Following Koenker and Bassett [1978], the θth regression quantile, $0 < \theta < 1$, is defined as any solution to the minimization problem:

$$\min_{b \in \Re^k} \left[\sum_{t \in \{t: y_t \geq x_t b\}} \theta \left| y_t - x_t b \right| + \sum_{t \in \{t: y_t < x_t b\}} (1-\theta) \left| y_t - x_t b \right| \right] \tag{6}$$

where K is the number of regressors. The least absolute error estimator is the regression median (that is, the regression quantile for $\theta = 1/2$). If there are T observations, at least $T\theta$ observations will be below the θth regression quantile hyperplane and at most $T\theta + K$ observations above it [Koenker and Bassett, 1978]. The results can be interpreted as the marginal effect on the θth quantile and not on the mean, as in the least squares case. The regression quantile results are important given that our dependent variable is the log of hourly wages and that this variable has a distribution with a long right tail.

The quantile regressions for quantiles 0.30, 0.50, 0.60, 0.95 and 0.98 are shown in Table 4. Note that the coefficients for $w_{h\text{-}hat}$ in the odd number columns (they do not include the education of generation 1) is increasing from 0.567 in quantile 0.30 to 1.077 in quantile 0.98. That is, while the hourly wage of children in quantile 0.30 increases by 0.567 percent as the expected hourly wage of parents increases by one percent, for children in quantile 0.98 the increase equals 1.077 percent.

When the education of the children is included in the regression, the coefficients for the hourly wage of parents rise from 0.30 in quantile 0.30 to 0.54 in quantile 0.98, but the reduction in the coefficient is larger for the top quantiles. This may also reflect the effect of parents' education endowment on children education.

Additionally, notice that the return to children's schooling increases as we move from lower to higher quantiles. In fact, as the correlation between schooling and the hourly wage is positive, this result accords well with recent estimations of the return to education in Mexico and some estimates for the United States. [Cragg and Epelbaum, 1995; Meléndez-Barrón, 1997; Valero-Gil, 1995; Welch, 1999].

Note that the increasing returns to schooling are specific to $w_{h\text{-}hat}$ and to edu_{ch}. They do not apply to the other factors included in υ_h or in the constant. In the last two, "personal factors" are included, while $w_{h\text{-}hat}$ only includes the effect of education of generation 0.

In terms of public policy, the tradeoff seems clear: more government spending on higher education could be efficient because it has the highest returns; however, more efficiency in this case will lead to a more unequal income distribution in the near future. On the other hand, more public investment in basic education, albeit slightly less efficient, will nonetheless tend to alleviate problems of income distribution in future generations.

CONCLUDING REMARKS

We studied the relationship between the labor market earnings of parents and their children. We were able to analyze separately the returns of parental education on the wages of children, taking into consideration the education of children. The main finding is that the relationship between the estimated wage of parents and their children is significant and positive. We also examined these relationships by family labor income levels. We found that the returns of parents' education to children's wage increases with the level of family income. This result is worrisome because it means that the return to the population average wages is lower for higher income families. The result is also important because, if the government spends more on higher education, we are probably going to generate income distribution problems in the next generation. We also found that children in higher income families have higher returns to education compared to children in poor families, even after controlling for the wage of the head of the family.

Using quantile regressions, we found again that the returns to schooling and to the estimated wage of parents are increasing as we move to the right side of the distribution. As such, more able individuals have higher returns to their education and to the education of their parents.

The results from this study have important public policy implications. Subsidies to higher education seem to be efficient because they have relatively high returns, but they lead to more income inequality not only in this generation but also in the coming generations. Alternatively, subsidies to primary and secondary education are not as efficient because they have lower return levels, but they are important if increasing intergenerational mobility in the earnings distribution is a social goal.

NOTES

The authors thank José Pagán for useful comments.

1. Recall that we have excluded cases for children with less than two years of experience and with less than 20 weekly hours of work.
2. This value differs from the value given in column 4 of Table 1 (0.345) because we are restricting the sample to children working at least 20 hours a week.
3. This coefficient can be interpreted as the ratio between the returns to schooling of the head on the children's income and the return on the income of the head. If Y is the income of the head and X is the income of his son, we can write $Y_{est} = \alpha_0 + \alpha_1 Edu + \alpha_2 Exp$ and the regression $X = \beta_0 + \beta_1 Y_{est} + \beta_2 Exp + \varepsilon$. If we run X against parents' education, $X = (\beta_0 + \alpha_0\beta_1) + \alpha_1\beta_1 Edu + (\alpha_2\beta_1 + \beta_2)Exp + \varepsilon$ we obtain $\beta_1 = \alpha_1\beta_1/\alpha_1 = (\partial X/\partial Edu)/(\partial Y_{est}/\partial Edu)$. Running those regressions we obtained $\alpha_1 = 0.1055$, $\alpha_1\beta_1 = 0.0710$ and $\beta_1 = 0.673$; β_1 is very near to the coefficient for $w_{h\text{-}hat}$ shown in column 3 of Table 2.
4. Using the Heckman two-step model we obtain a coefficient of 0.768 for $w_{h\text{-}hat}$ and 0.223 for υ_h in column 5 of Table 2. The coefficients of Table 2 are obtained selecting people with 20 or more hours of work and more than one year of experience and we cannot do that using the Heckman's model because we would be using multiple forms of self-selection.
5. In the first generation, the trend towards the mean is 0.721; for the second generation, the earnings convergence is 0.5198 (0.712×0.712); for the third generation, this is 0.3748 (0.5198×0.712); and for the fourth generation, it is 0.2702 (0.3748×0.712).
6. The exchange rate was 9.50 pesos per U.S. dollar in the sampling period.
7. This assumes that the correlation between years of education and earnings is positive, as it is usually the case.

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